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Facial Gender Recognition Using Eyes Images

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Abstract: In the last decade, computer vision and pattern recognition field draw more attention; Facial gender classification can significantly improve human identification. It is useful in many applications that make use of the gender information. This paper proposes a novel feature extraction technique that used only the eye and eyebrow region to extract the features will be used in the gender classification. The proposed technique was consisting of several steps. The first step was to crop the eye area from the image as a pre-processing. Then apply one of the feature extraction methods: 2D-Wavelet Transform, Gray Level Co-occurrence Matrix and Discrete Cosine Transform. Finally, use SVM in the classification step to get the results. The proposed method obtained accuracy rate of 99.49 % on gender recognition using 2D-Wavelet Transform, accuracy rate of 98.49 % on gender recognition using GLCM and 99.62 % with DCT on Faces94 database.

Keywords: Gender recognition, feature extraction, 2D-Wavelet Transform, Gray Level Co-occurrence Matrix, Discrete Cosine Transform, Support Vector Machine

I. INTRODUCTION

In the past 40 years, there has been a significant interest of using pattern recognition in many emerging applications such as feature extraction, description of patterns and classification [1], this increased the need for more theoretical methods and experimental software in this field to be embedded in the design of pattern recognition applications which are challenging and demands more computations, such as data mining, classification and biometric authentication (i.e. face recognition, eye recognition, fingerprint and iris matching) [2].

Automated facial gender recognition has become an interesting and challenging research problem in recent years. Nowadays, researchers paid more attention to gender recognition in many potential application fields such as biometric authentication and passive demographic data collection. Facial gender classification can significantly improve human identification in biometric recognition by speeding and increasing the accuracy as it reduces the process of matching the face in the databases to nearly the half and helps in potential applications in security industry and human computer interaction. Gender classification can be done by using different methods such as classifying the gait, the eye iris and the hand shape. However, the most suffusion techniques for gender classification were always standing on facial features.

Mostly all the images from databases need some kind of preprocessing [3]. We often need to segment the interest regions from the background [4], such as, eyes and face detection. After applying a necessary preprocessing, the image is ready for facial feature extraction. L. Zheng et al. [4] stated that the features should be easily computed, robust, insensitive to various distortions and variations in the images, and rotationally invariant.

In general, there are many types of features could be extracted from facial images: The most common features are the geometric based features and the appearance based features [3]. Geometric based features have clear physical meaning such as, nose, mouth and size of the eyes; while appearance based features has no physical meaning and extracted from the whole face segment [4] [5]. Some studies proposed hybrid gender classification method using a combination of appearance features and geometry features [6] [7]. In [8] M. A. Berbar proposes a texture features extraction technique that based on using the grey-level co-occurrence matrix (GLCM) that used to extract second-order texture features and obtained good accuracy.

Some studies used some parts of the face to extract the features, in [9] each face image was described by an LBP histogram of bins then Adaboost was used to learn the discriminative LBP histogram bins for better gender classification. They observed that the most discriminative in gender recognition LBPH bins features are distributed in the regions around and above the eyes manly. Also O. Ozbudak, M. Kırcı et al. [10] studied the different facial and racial

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information and stated that some facial features like eyes and forehead are more influential in gender classification process.

In this paper we introduce a gender classification system that used three features extraction techniques which are GLCM, DCT and DCT. The flowchart of the framework is shown in Figure. 1. First, in the preprocessing stage, the eye region is detected and cropped. Then the feature extraction stage, the features are extracted from the eye regions using one of the proposed features extraction techniques. After that, the classifier training stage using SVM. Finally, the result for gender prediction is obtained after the testing stage.

The rest of the paper is organized as follows. In Section 2, we introduce the proposed methodology. Then the experimental results introduces in Section 3.

II. PROPOSED SYSTEM

Any classification system must be done in three main steps: preprocessing, feature extraction, and classification. Figure 1 shows a detailed block diagram of the complete design of the system.

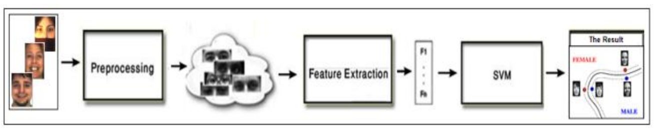

Figure. 1. The proposed gender classification system

1.1 Pre-processing

As a pre-processing, the eye area will be detected and cropped. First, the skin area will be detected to exclude the background and the hair or scarf information, we will use a colour components based technique that was proposed in [11] which introduces a hybrid colour model to classify skin colour pixels. It uses the HSL, RGB and CMY colour models. After detecting the skin area we will crop on the bounding box around the face. Then, we will take the horizontal histogram of the red layer of the face image. After that, we will locate the peak that responsible of the eyes region. Finally, crop around the area of the eyes to get the final images. Figure. 2 shows the steps of the pre-processing.

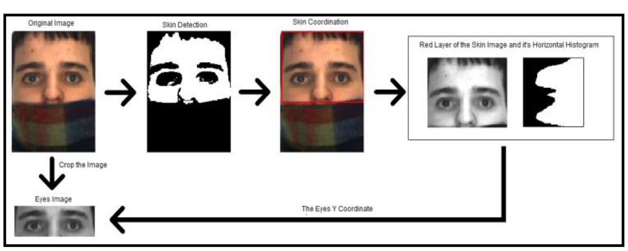

Figure 2 Image Preprocessing Steps

1.2 Feature Extracting

We will extract the features from the images using three techniques: 2D-wavelet transform, DCT and the GLCM.

1.2.1 2D-Wavelet Transform

After doing some necessary preprocessing on the images, the 2D-Wavelete Transform will be applied on the images which will return the wavelet decomposition of the image in a specified level. It detects the image's attribute which considered as the features that will be used in the classification step, proposed in [8].

We intend to work with the wavelet coefficients features at different levels of decompositions and with taking different ratios of the extracted features after arranging them in ascending order then choosing the highest features. The 'db8' daubechies 8 Wavelets will be used as the mother wavelet to extract the features.

1.2.2 Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) takes an image and estimates its properties related to the second-order statistics. It takes two pixels and a spatial relation between them (distance d and direction) and gives the corresponding number of occurrences of the pair of gray levels. To estimate the similarity between different Gray Level Co-occurrence Matrices, we will apply GLCM with different directions and distances. Also we will apply the GLCM with different number of gray levels, introduced in [8].

We intend to work with different directions and distances until we got good results to prove which one is better according to the experiment. We will work with the 22 features can be extracted from GLCM according to Haralick [12], then got transferred to the SVM to be classified.

1.2.3 Discrete Cosine Transform

The DCT decomposes a signal into its elementary frequency components. The technique based on decomposing the image into blocks and from each block we calculate its DCT. After that, decompose the DCT block to smaller blocks and then calculate the average of these block which considered as the features of that block. Figure. 3 shows the steps.

This technique abbreviated the features of the DCT by getting only one value for each block from the DCT matrix. The algorithm as follow:
-Resize the images.
-Divide the image into blocks.
-Calculate the DCT for each block.
-Divide the DCT matrix into blocks.
-Take the average value for each block.

1.3 Classification with Support Vector Machine

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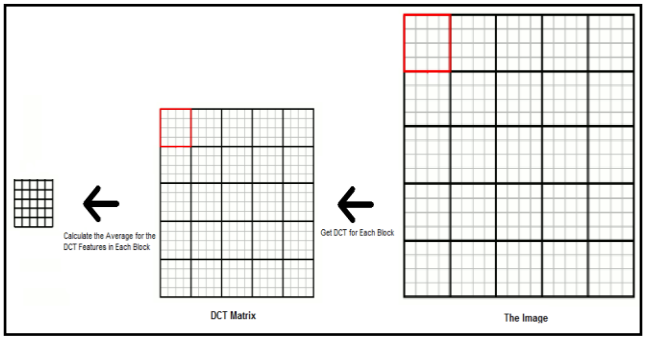

Figure 3 Steps of the DCT decomposing process

To classify the feature vectors obtained from the Wavelet, GLCM and DCT coefficients, we employ in this study the SVM to find the optimal hyper plane with maximum margin that separates the unknown input image into certain class. The Support Vector Machine (SVM) as a classifier has been used more often in the gender classification problem and has been proved in many studies that it's a superior in the pattern classification. It takes feature vectors extracted from images as input and it gives the class this image belongs to (Males, Females) as its output. It's a kernel based approach and the accuracy of the SVM is affected by the kind of the kernel function has been chosen and using a suitable kernel may lead to good accuracy [13]. We used the SVM with the Radial Basis Function (RBF) because it has proven to have fewer numerical difficulties [11]. We will use the 2-fold cross-validation for training and testing.

1.4 The Measurements

We estimated the results standing on some special measures. We measure the accuracy obtained by taking the ratio between the numbers of images that are classified correctly to the total number of images. The specificity (equation 1), the sensitivity (equation 2), and the accuracy (equation3).

$$\text{Specificity (Males recognition)}\,\text{MR}\% = \frac{\text{Number of males images classified correctly}}{\text{Total number of males images}} \quad (1)$$

$$\text{Sensitivity (Females recognition)}\ \text{FR}\% = \frac{\text{Number of females images classified correctly}}{\text{Total number of females images}} \quad (2)$$

$$\text{Accuracy ACC}\% = \frac{Number\ of\ images\ classified\ correctly}{Total\ number\ of\ images} \quad (3)$$

III. Results and Discussion

1.5 Setup of Experiments

To verify the proposed Feature extraction methods, we used AR database [14] in our experiment. Our data set consists of 1982 images (991 males, 991 females). Eye area got detected and cropped according to the proposed technique. We excluded the images with sunglasses since our project aims to work on the area of the eye and eyebrow, there were 300 images in the male and 299 in the female with sunglasses. Before extracting the features the eye images are normalized to 64 × 64 or 256 × 256.

Also we used faces94 database [15] in our experiment. Our data set consists of 798 images (399 males, 399 females). The region of the eyes and eyebrows was cropped manually. Eye images are normalized to 64 × 64 then transformed to grey-scale before extracting the features.

Figure 4 Eyes Image after Detection and Cropping

We test the proposed system with 2-fold cross validation. The training and testing samples are selected randomly. The images got fold randomly then separate them in half. It simply folds the dataset then separates it in 2 halves. The first one is used in the training phase where a model is produced. And the second one is tested using the model from the training Phase. Then alternatively the two halves got exchanged where the training dataset used now for testing and vice versa.

1.5.1 Eye Detection and Cropping

We apply the technique proposed in the last section to detect and crop the eye and eye brow area on AR database, after several trials and by experiment; we notice that the eye and eye brow area gave a noticeable peak and we were succeeded in locating the peak throughout the histogram. The eye detection technique gave good results. It succeeded by 99%. Figure. 4 Shows some images after the cropping process.

1.5.2 2D Wavelet Transform

The aim of this experiment was to monitor the accuracy at different ratio for feature selection also different levels of decomposition used in the 2D-WT on Faces94 database. The eye images were resized to 64 by 64 pixels before extracting the features. When we obtain our first experiment with (level = 4) and different ratio we noticed that the accuracy nearly stabled at the ratio 60, this gives us a hint that the features above the ratio 60 are redundant and doesn't have a big effect on the accuracy. After that we apply the feature extraction with different levels after we fix the ratio on 60% and notice that the accuracy was the best at level 8, although it has a good accuracy at level 4. Finally, we apply the

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feature extraction with different ratio with level 8, and this experiment gives the best accuracy throughout our experiments (Table 1 shows the results in different ratio with level = 8).

Table 1 Results for classification using 2D WT

Ratio	log2c	log2g	Sensitivity	Specificity	Accuracy
10%	17	-17	94.808	97.535	96.115
20%	16	-17	95.550	100	97.744
30%	16.5	-17	96.531	99.210	97.869
40%	16.5	-17	97.320	100	98.621
50%	17	-17	97.033	100	98.496
60%	17	-17	97.559	100	98.746
70%	16	-17	96.578	99.760	98.120
80%	17	-17	97.751	99.258	98.496
90%	17	-17	99.497	99.497	99.498

1.5.3 DCT

The aim of this experiment was to monitor the accuracy with different sizes of the decomposed.

1.5.3.1 Case 1

-Resize the image to 256 × 256
-Decompose the image to 8 × 8 blocks
-Calculate DCT for each block
-Decompose the DCT matrix to 4 × 4 blocks
-Calculate the average of the block
-Take the average as feature for the block
The result for applying case 1 on AR database shown in table 2

Table 2 Results of applying DCT using Case 1 on AR DB

log2c	log2g	Sensitivity	Specificity	Accuracy
8.5	-17	90.037	91.44	90.71
7.5	-17	90.449	91.25	90.81
7.5	-17	90.449	91.25	90.81

The result for applying case 1 on Faces94 database shown in table 3.

Table 3 Results of applying DCT using Case 1 on faces94

log2c	log2g	Sensitivity	Specificity	Accuracy
2	-17	98.038	100	98.99
4	-17	99.497	99.736	99.62
4	-17	99.497	99.736	99.62

1.5.3.2 Case 2

-Resize the image to 256 × 256
-Decompose the image to 4 × 4 blocks
-Calculate DCT for each block
-Decompose the DCT matrix to 2 × 2 blocks
-Calculate the average of the block
-Take the average as feature for the block
The result for applying case 2 on AR database shown in table 4

Table 4 Results of applying DCT using Case 2 on AR DB

log2c	log2g	Sensitivity	Specificity	Accuracy
8	-17	90.45693333	91.14541272	90.7669021
7.5	-17	90.56175513	90.95086019	90.716448
8	-17	90.45693333	91.14541272	90.7669021

The result for applying case 2 on Faces94 database shown in table 5

Table 5 Results of applying DCT using Case 2 on faces94 DB

log2c	log2g	Sensitivity	Specificity	Accuracy
2	-17	98.03827751	100	98.9974937
4	-17	99.49760766	99.73684211	99.6240602
4	-17	99.49760766	99.73684211	99.6240602

1.5.4 GLCM

The aim of this experiment was to monitor the accuracy at different spatial relations between the two pixels (distance d and direction θ) with level = 8, which will determine the size of the GLCM matrix. We apply the technique on AR database and Faces94 database. The eye images were resized to 64 by 64 before applying GLCM on them.
We work with direction of 90 º and 0 º; and not 45º and 135º because it has been proven in [8] that it doesn't give good results.
In the following the results of the experiment with direction 90 º and different distances on AR database. (Table 6 shows the results with different distances).

Table 6 Accuracy of GLCM with Different Distance and 90 º on AR DB

Dis	log2c	log2g	Sensitivity	Specificity	Accuracy
12	17	-17	71.1988841	70.0903017	70.534813
14	17	-17	70.4131284	71.5125338	70.837538
16	14.5	-17	68.2126863	74.3125403	71.089808
20	14	-17	68.1380466	75.0982959	71.442987
22	17	-17	73.3624143	69.9108403	71.493441
28	16.5	-17	75.524313	69.4387343	72.452069
30	17	-17	75.4647644	70.8458752	73.107972

In the following the results of the experiment with direction 0 º and different distances on Faces94 database. (Table 7 shows the results with different distances). We noticed that

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the accuracy is improved as we increase the distance and the 0 º direction gave better accuracy than 90 º.

Table 7 Accuracy of GLCM with Different Distance and 0 º on Faces94 DB

Dis	log2c	log2g	Sensitivity	Specificity	Accuracy
30	17	-17	94.3062201	97.27272727	95.7393484
40	17	-17	95.26315789	98.30143541	96.7418546
50	17	-17	97.46411483	99.49760766	98.4962406
56	17	-17	97.32057416	99.76076555	98.4962406

IV. CONCLUSION

In the last few years, using computer vision and pattern recognition increased in many studies and systems. Facial gender classification can improve human identification. The idea of our proposed feature extraction technique that works only with the eye and eyebrows region of the person. The proposed technique consists of several steps. The first step was to crop the eye area from the image using some processing. Then apply one of the proposed feature extraction methods: 2D-Wavelet Transform, DCT and GLCM. Finally, Use the SVM in the classification step. We conduct an experiment using feature extraction techniques and the proposed method has produced promising results. We obtain accuracy rate of 99.49 % on gender recognition using 2D-Wavelet Transform, accuracy rate of 98.49 % on gender recognition using GLCM and 99.62 % with DCT on Faces94 database. The DCT gave the best results over the two face databases we have used.

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